EGTRIB Journal
JOURNAL OF
THE EGYPTIAN SOCIETY OF TRIBOLOGY
VOLUME 17, No. 2, April 2020, pp. 13 - 22 ISSN 2090 - 5882
(Received December 22. 2019, Accepted in final form February 07. 2020) www.egtribjournal.com

SURFACE ROUGHNESS PREDICTION IN HARD-TURNING WITH ANN AND RSM

Ahmed A. Elsadek, Ahmed M. Gaafer and S.S. Mohamed

**Department of Mechanical Engineering, Faculty of Engineering at Shoubra,
Benha University, Cairo, Egypt.**

ABSTRACT

In the below investigation, artificial-neural-network (ANN) and response-surface-methodology (RSM) predictive tools shall be applied for predicting "surface roughness" on hard-turning of AISI H13 hot work steel. The mean relative error shall be utilized for testing the appropriateness of the created predictive models. Also, the influence of hardness of workpiece in addition to speed, feed and "depth of cut" on the surface roughness will be highlighted. The outcomes showed that the mean relative error for the RSM predictive model was 5.07% while the ANN model yielded a mean relative model of 2.21%. Besides, it was revealed that the feed then the workpiece hardness are the terms possessing the greatest influence terms on investigating the surface roughness in hard-turning. Where the feed rate increases the surface roughness while the workpiece hardness reduces it.

KEYWORDS

Response surface methodology, artificial neural network, hard turning, Surface roughness.

INTRODUCTION

Hard-turning is gaining importance as a pre-grinding process, because of its lower costs when compared with grinding owing to avoiding employing the grinding- wheels which costs more than hard-turning tooling, which is done on ordinary turning lathes. [1] Hard-turning is the process of turning workpiece having the hardness of 45–68 HRC [2], into finished components. The best benefit of hard-turning is reducing the machining time as well as improving the products quality in addition to other advantages stated in literature. [3–7] Among the various important applications of hard-turning is molds manufacturing, in which complicated geometries are cut in high hardness materials. Where short lead time along with high quality products are among the challenges that faces manufacturers. The product quality is becoming more significant owing to the strengthened industrial competitions and product quality realization. Thus the major consideration in machining industry is improving the whole performance of the cutting process. Javidi et al. [8] investigated the impact of feed rate and tool nose radius on maximum surface roughness. Ozel [9] "investigated the impact of workpiece hardness and cutting tool geometry on surface roughness on turning AISI H13 tool steel". Elsadek et al. [10] applied fuzzy logic for roughness and tool wear prediction. Rangwala and Dornfeld [11] employed ANN for predicting the turning performance". Kant et al. [12] joined the ANN along with genetic-algorithm (GA) for surface roughness prediction and optimization. Mia and Dhar [13]

utilized ANN and RSM in predicting cutting temperature in dry and under high pressure coolant. They found that in some cases the RSM showed a higher prediction capability compared with ANN. Other researchers observed that ANN is better than RSM in prediction [14-15] all the time. Consequently, more research is needed to compare between the two models. Thus, the aim of the current work is discussing important aspects including the effect of cutting-parameters in addition to the workpiece hardness on the generated surface finish in hard-turning in addition to utilizing artificial intelligence and statistical techniques in implementing an efficient predictive model that is capable of predicting the surface roughness response based on the input parameters.

EXPERIMENTAL MATERIALS

Round bars of diameter 35 mm and 100 mm length of AISI-H13 tool steel hardened to 45±1, 50±1 and 55±1 HRC were utilized as workpieces. Table 1 shows the chemical composition of the employed alloy. A mixed ceramic insert of designation CNGA 120408 E040 was mounted on a negative rake angled shank. Dry turning tests were performed on a conventional lathe due to environmental concerns [16]. Surftest SJ-310", Make: MITUTOYO was employed for surface roughness measurement.

Table 1. Chemical Composition of AISI-H13 workpieces

Element	C	Mo	V	Mn	Mo	Cr	Si	S	P
%	0.390	1.250	0.920	0.48	1.250	4.88	1.09	0.002	0.012

Experimental Design

Response surface central-composite-design was employed for experimental design. The factors and factor levels are shown in table 2. Experiments were done and the results were reported. The experimental plans were established for the setting up of linear models for roughness. Table 3 reveals the planned experimental runs as proposed by the design.

Table 2. The factors and factor levels

Factors	Levels		
Cutting Speed "v"(m/min)	100	125	150
Feed Rate "f" (mm/rev)	0.05	0.10	0.15
Depth of Cut "d" (mm)	0.05	0.09	0.13
Hardness "h" (HRC)	45	50	55

Table 3. Planned Experimental runs

Run	Speed m/min	Feed mm/rev	Depth of cut mm	Hardness HRC	Run	Speed m/min	Feed mm/rev	Depth of cut mm	Hardness HRC
1	100.00	0.15	0.13	45.00	16	100.00	0.05	0.05	45.00
2	100.00	0.05	0.13	55.00	17	125.00	0.10	0.09	50.00
3	150.00	0.05	0.13	45.00	18	125.00	0.15	0.09	50.00
4	125.00	0.10	0.09	50.00	19	125.00	0.05	0.09	50.00
5	150.00	0.05	0.13	55.00	20	125.00	0.10	0.09	50.00
6	125.00	0.10	0.09	50.00	21	150.00	0.15	0.13	45.00
7	150.00	0.15	0.05	55.00	22	150.00	0.05	0.05	45.00

8	**125.00**	**0.10**	**0.05**	**50.00**	**23**	**125.00**	**0.10**	**0.09**	**50.00**
9	**100.00**	**0.15**	**0.13**	**55.00**	**24**	**100.00**	**0.15**	**0.05**	**45.00**
10	**150.00**	**0.15**	**0.05**	**45.00**	**25**	**100.00**	**0.05**	**0.13**	**45.00**
11	**100.00**	**0.05**	**0.05**	**55.00**	**26**	**100.00**	**0.15**	**0.05**	**55.00**
12	**125.00**	**0.10**	**0.09**	**55.00**	**27**	**125.00**	**0.10**	**0.13**	**50.00**
13	**100.00**	**0.10**	**0.09**	**50.00**	**28**	**125.00**	**0.10**	**0.09**	**50.00**
14	**150.00**	**0.05**	**0.05**	**55.00**	**29**	**150.00**	**0.10**	**0.09**	**50.00**
15	**125.00**	**0.10**	**0.09**	**45.00**	**30**	**150.00**	**0.15**	**0.13**	**55.00**

RESULTS AND DISCUSSION

Analysis of variance (ANOVA) was utilized in testing the adequacy of the proposed model, table 4. The linear-model has an F-Value of 19.67, which indicates its significance. The linear model generated by the "design can be represented" by the following equation:

$$Yu = \beta o + \sum_{i=1}^{n} \beta i \, xi + e \qquad (1)$$

Where Yu is the required response (roughness), βo, β1... βi are the regression coefficients, 'x' is the "independent variables" and 'e' is the error. The above mentioned equation can be written to represents the roughness linear-model in terms of the above mentioned factors in the form of actual factors as follows:

Roughness "Ra" = 3.1351861 - 0.0027089 * Speed + 5.29222 * Feed

+ 1.101389 * "Depth of Cut" - 0.024378 * Hardness (2)

Table 4 ANOVA results for roughness

Source	Sum of Squares	df	Mean Square	F-value	p-value	Contribution
Model	**1.65**	**4**	**0.4113**	**19.67**	**< 0.0001**	**76%**
A-Speed	**0.0826**	**1**	**0.0826**	**3.95**	**0.0580**	**3.80%**
B-Feed	**1.26**	**1**	**1.26**	**60.28**	**< 0.0001**	**58%**
C-Depth of Cut	**0.0349**	**1**	**0.0349**	**1.67**	**0.2079**	**1.61%**
D-Hardness	**0.2674**	**1**	**0.2674**	**12.79**	**0.0015**	**12.32%**
Residual	**0.5227**	**25**	**0.0209**			
Lack of Fit	**0.4515**	**20**	**0.0226**	**1.59**	**0.3214**	**20.8%**
Pure Error	**0.0712**	**5**	**0.0142**			
Cor Total	**2.17**	**29**				

It is clear from table 4 that both feed and hardness are statistically significant terms with contribution percent of 58% and 12.32% respectively while speed and depth of cut are insignificant terms. Similar findings were obtained by [17, 18] Inspecting the residuals is essential for testing the established model for adequacy. This analysis of residuals is necessary for confirming that assumptions for ANOVA are being met. Figure 1, reveals the residuals against run test. The figure shows that the value points are randomly distributed. The value points do not take a definite shape which is desirable. Furthermore, Figure 2 shows the predicted response vs the actual values in which the points of the predicted response and the actual value points are randomly distributed along a 45° line. This also indicates that the established model is adequate and there is no

reason to suspicious any constant variance [19]. Then the suggested model is satisfactory and can be utilized as it comply with previous works.

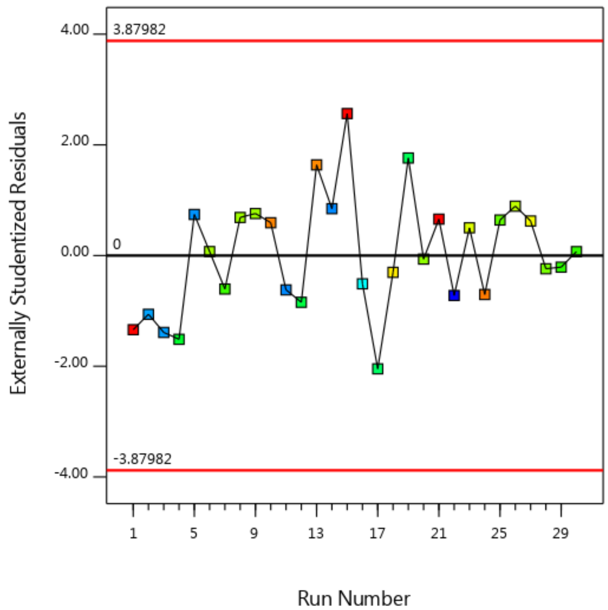


Fig. 1 Residuals against run tests for surface roughness.

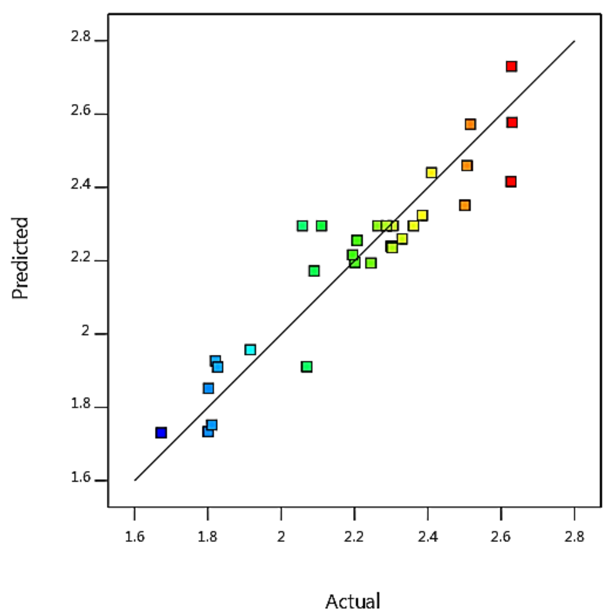
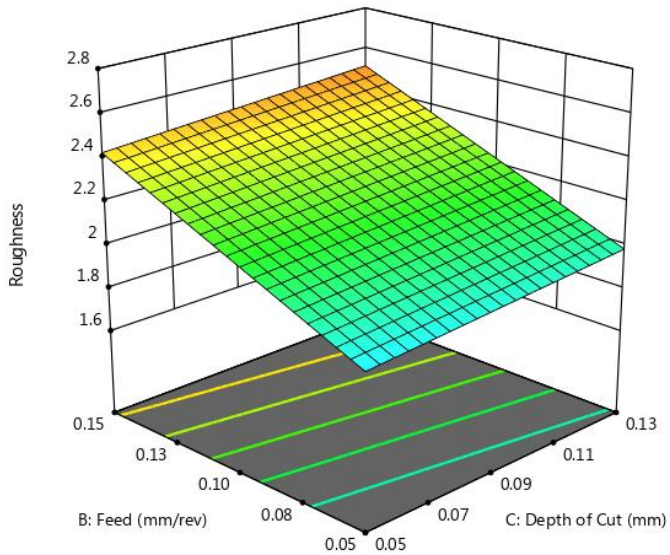


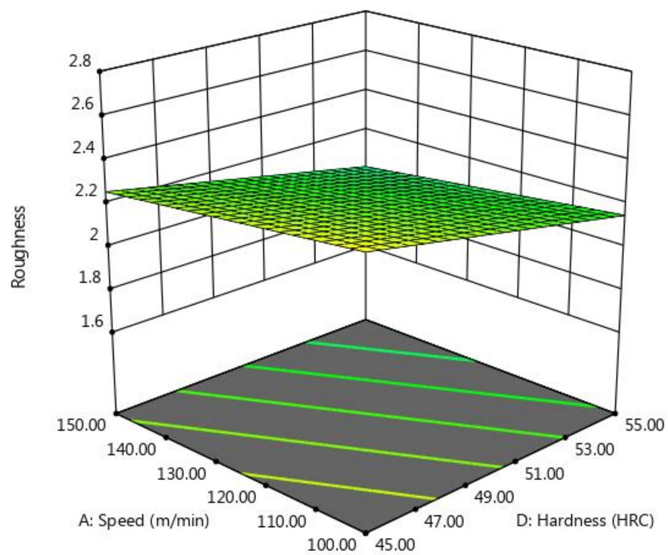
Fig. 2 Predicted response vs the actual values for surface roughness.

Figure 3 (a-b) reveals the 3D response surface curves for surface roughness. Where Figure 3a reveals that the best roughness value can be obtained at the combination of the least feed rate and depth of cut values. While Figure 3b reveals that surface finish is improved by utilizing the maximum values of speed and workpiece hardness. It is clear

that the outcomes of the 3D plots agrees with statistical analysis.



(a)



(b)

Fig. 3 (a, b) 3D response surfaces curves for the surface roughness.

Artificial Neural Network

ANNs, are used for developing models in a similar way in that brains of humans treat information. The architecture, training algorithm, number of neurons, functions, weights and biases impact the accurateness of the ANN model. In the present work, feedforward back propagation network was utilized. Four nodes in the input layer representing speed

(v), feed (f), "depth of cut" (d) and workpiece hardness (h) and one node for the output layer representing the predicted response that is the roughness. Figure 4. Reveals the structure. ANN predictive model is based on trial and error for finding the best results. The chosen parameters after trial and error are shown in Table 5. MATLAB R2015a 'nntool' toolbox was employed for training and testing the ANN. Testing the adequacy of the ANN predictive model RSM was employed. RSM predicts results based on the linear model illustrated in equation 2. Table 6 reveals the experimental and the corresponding RSM, ANN predicted values as well as the relative error for each.

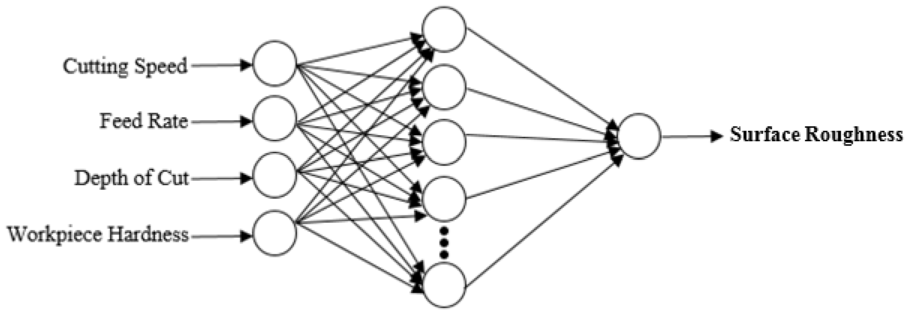


Fig. 4 Surface roughness neural network structure.

Table 5 Selected ANN parameters for surface roughness prediction

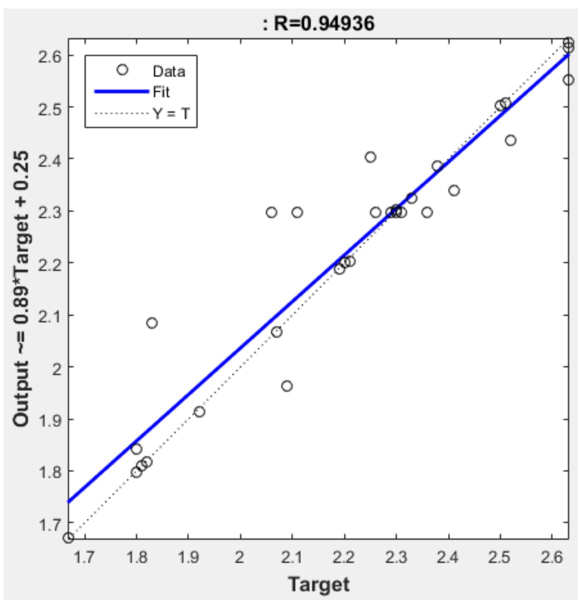
Chosen ANN parameter	Value
Network structure	4-9-1
Training/testing data	24/6
Network algorithm	Feedforward back propagation
Transfer function	Tansig, Purelin
Training function	Traingdx
Learning function	Learngd
Performance function	MSE
Momentum constant	0.9
Learning rate	0.01

Regression plot between the experimental and predicted values for roughness by ANN and RSM is shown in Figure 5a and Figure 5b respectively. The value of regression coefficient is 94.946% for ANN and 87.212% for RSM that shows that ANN is more adequate in predicting surface roughness in hard-turning compared with RSM. The mean relative error for the ANN model was 2.21% while that for RSM is 5.07%. Consequently, the generated ANN model can effectively predict the response with a slight error. Figure 6 shows the scatter plot comparing the experimental and predicted values for both RSM and ANN respectively. It shows that ANN predicted value points at different runs are much closer to the experimental values than the value points predicted by RSM.

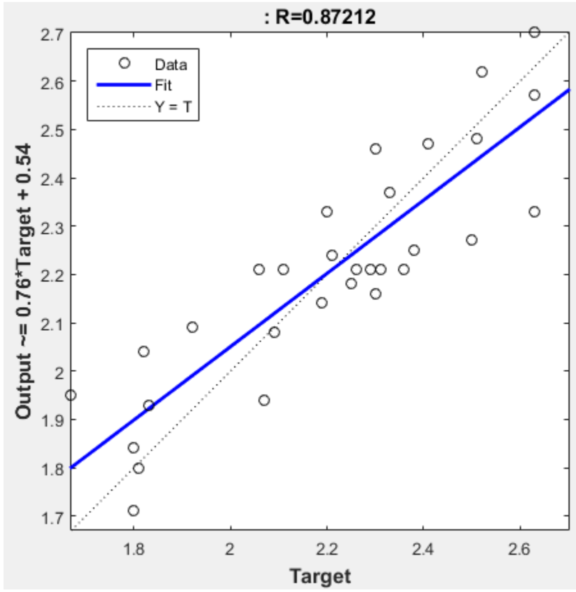
Table 6 Predicted values and corresponding relative errors for RSM and ANN modelling techniques for surface roughness.

Run	Surface roughness (μm)			Relative Error (%)	
	Experimental	RSM	ANN	RSM	ANN

1	**2.63**	**2.7**	**2.624**	**2.662**	**0.152**
2	**1.83**	**1.93**	**2.085**	**5.464**	**14.122**
3	**1.82**	**2.04**	**1.818**	**12.088**	**0.165**
4	**2.11**	**2.21**	**2.296**	**4.739**	**8.815**
5	**1.81**	**1.8**	**1.809**	**0.552**	**0.110**
6	**2.31**	**2.21**	**2.296**	**4.329**	**0.390**
7	**2.21**	**2.24**	**2.204**	**1.357**	**0.136**
8	**2.3**	**2.16**	**2.303**	**6.087**	**0.000**
9	**2.3**	**2.46**	**2.298**	**6.957**	**0.087**
10	**2.51**	**2.48**	**2.507**	**1.195**	**0.000**
11	**1.8**	**1.84**	**1.843**	**2.222**	**2.275**
12	**2.09**	**2.08**	**1.962**	**0.478**	**6.124**
13	**2.5**	**2.27**	**2.503**	**9.200**	**0.080**
14	**1.8**	**1.71**	**1.798**	**5.000**	**0.167**
15	**2.63**	**2.33**	**2.615**	**11.407**	**0.457**
16	**1.92**	**2.09**	**1.913**	**8.854**	**0.157**
17	**2.06**	**2.21**	**2.296**	**7.282**	**11.565**
18	**2.41**	**2.47**	**2.339**	**2.490**	**2.946**
19	**2.07**	**1.94**	**2.066**	**6.280**	**0.193**
20	**2.29**	**2.21**	**2.296**	**3.493**	**0.394**
21	**2.63**	**2.57**	**2.553**	**2.281**	**2.928**
22	**1.67**	**1.95**	**1.671**	**16.766**	**0.120**
23	**2.36**	**2.21**	**2.296**	**6.356**	**2.753**
24	**2.52**	**2.62**	**2.436**	**3.968**	**3.180**
25	**2.25**	**2.18**	**2.404**	**3.111**	**7.082**
26	**2.33**	**2.37**	**2.325**	**1.717**	**0.215**
27	**2.38**	**2.25**	**2.387**	**5.462**	**0.084**
28	**2.26**	**2.21**	**2.296**	**2.212**	**1.413**
29	**2.19**	**2.14**	**2.188**	**2.283**	**0.319**
30	**2.2**	**2.33**	**2.200**	**5.909**	**0.045**



(a)



(b)

Fig. 5 Regression Plot for a. ANN and b. RSM.

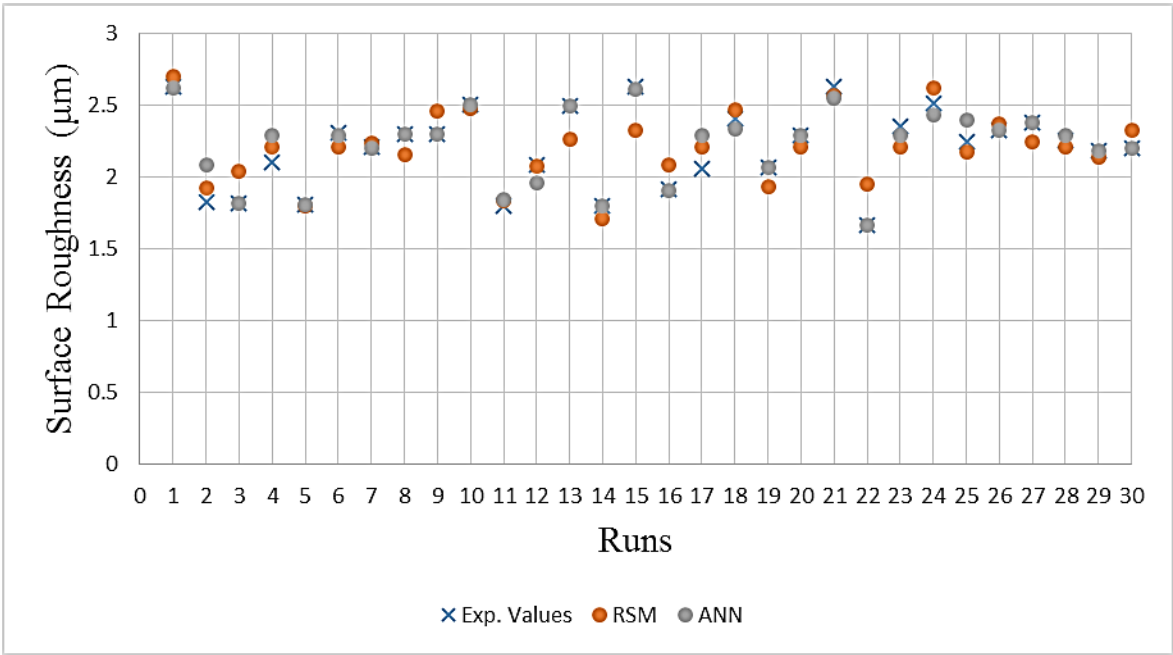


Fig. 6 Experimental versus the predicted values of surface roughness using ANN and RSM.

CONCLUSIONS

This research aims to highlight the influence of workpiece hardness in addition to speed, feed and depth of cut on the surface roughness in "hard-turning". Furthermore, predictive models for predicting the values surface roughness in "hard-turning" were formulated utilizing ANN and RSM. Linear model was employed and tested by ANOVA. And the below can be concluded:

1. Workpiece hardness plays an important role in improving the surface roughness in hard-turning. On the other hand, feed rate was found to possess the major negative effect on it, such that to hard turn a part with the best possible surface quality, the feed rate values must be kept as low as possible.

2. ANN predictive model proved its appropriateness and adequacy over the RSM model for each individual response, based on the vales of the mean relative error and the regression coefficient values.

3. ANN can be used effectively in implementing an efficient predicting system so as to be able to predict precise values of the outcome responses based on the input values of cutting parameters and workpiece hardness, in hard-turning operations.

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